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Toward a BICA-Model-Based Study of Cognition Using Brain Imaging Techniques

Vadim L. Ushakov[1,2] and Alexei V. Samsonovich[1,3]

[1]*National Research Nuclear University MEPhI (Moscow Engineering Physics Institute), Moscow, Russian Federation*
[2]*National Research Center "Kurchatov institute", Moscow, Russian Federation*
[3]*Krasnow Institute for Advanced Study, George Mason University, Fairfax, VA, USA*
tiuq@yandex.ru, asamsono@gmu.edu

Abstract
The aim of this study is to develop an approach to evaluation of a biologically inspired, causal model of cognition that exposes the mechanistic requirements for achieving fluid intelligence and makes testable predictions of neurophysiological measures. In order to build human-level-efficient tools for data analysis, it is necessary to have a theory of how concepts are represented in the human brain. This theory should specify (a) the structure and semantics of concept representations in the human brain, and (b) types, formats and specific patterns of neuronal activity instantiating these representations. The key to a biologically-informed human brain model begins with the mapping of (a) to (b), i.e., of the emotional Biologically Inspired Cognitive Architecture (eBICA) to informative features and characteristics of brain activity. The result is a detailed description of the information processing level of the dynamics of emotional evaluation of other agents and relationships with them in the process of joint activities, and the role of this evaluation in decision-making and generation of behavior based on the selected emotional cognitive architecture.

Keywords: cognitive architecture, fMRI, functional connectivity, emotional cognition, semantic cognitive mapping

1 Introduction

In order to develop an approach to evaluation of a biologically inspired, causal model of cognition that exposes the mechanistic requirements for achieving fluid intelligence and makes testable predictions of neurophysiological measures, it is necessary to understand first what are the functional components of cognitive information processing in the brain, e.g., how concepts are represented in the

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human brain, and what sorts of intelligent activities occur in the brain that operate on those concepts. Therefore, we begin with a brief overview of these topics.

Fluid intelligence is one important aspect of human cognition. A defining characteristic of fluid intelligence is that it applies to problems that are novel in their components, challenges, and objectives. In essence, each problem must be solved in a unique manner, using techniques tailored to the specific problem. This implies that fluid intelligence is mediated by multiple capabilities or mechanisms that are configured for each unique problem. Here we use the following terminology: fluid reasoning, understood as adaptive reasoning and problems solving (ARP), requires fluid intelligence (measured by standard tests as a cumulative characteristic Gf) plus other cognitive abilities, such as the ability to form complex verbal associations. Fluid intelligence in turn depends on a number of factors, including the size of working memory, the executive function, cognitive decoupling, and more.

According to the standard theory [30], brain activity at rest is characterized by the default mode network (DMN). This network is suppressed during ARP, when the brain switches to the Gf network (GFN) supporting fluid intelligence. GFN involves many distributed parts of the brain and functional components, and this is why activation of working memory (or even more narrowly, short-term memory) alone is not sufficient for enabling fluid intelligence: it may succeed or may fail, as the literature demonstrates, depending on the engagement of other vital functional components in the network. Therefore, we need to activate the entire GFN in order to improve Gf. This is our main hypothesis underlying the design of the intervention and the choice of measures.

At a mathematical level, the above statements translate into the eBICA model and its components (Figure 1) supporting fluid reasoning that map onto components of the Gf network in the brain. eBICA is one of the models known as cognitive architectures [18], many of which are biologically inspired. It was developed at George Mason University [35] and sometimes is referred to as GMU BICA. The mapping of eBICA components into GFN provides the main prediction used in the intervention design and measures. We predict that activation of short-term memory alone is not sufficient for fluid intelligence. Instead, we need to engage certain functional components – elements of the BICA model, including components of working memory, semantic memory, the value system and the cognitive map.

The rest of the paper is organized as follows. First, we develop a conceptual framework that will allow us to map the formal model of cognitive architecture onto neural activity in different regions of the human brain. The model is based on the emotional Biologically Inspired Cognitive Architecture (eBICA) [39]. We define the mapping and make predictions based on it regarding cognitive processes which should be engaged when solving various cognitive tasks. We then propose experiments to map expected cognitive processes onto the human brain activity using available brain imaging techniques, such as fMRI. We conclude with discussing the proposed promising way toward an understanding of cognitive brain dynamics based on a biologically inspired cognitive architecture.

2 The Conceptual Framework

2.1 Overview of the eBICA Model

The general emotional Biologically Inspired Cognitive Architecture (eBICA) model is described in Figure 1. This model substantially extends the extended Baddeley working memory model [3]. Its components have been mapped to brain areas [35,37]. The eBICA model is based on three main building blocks: (i) a schema, which is a universal element of all representations in this model; (ii) a mental state, which is populated by bound instances of schemas and represents the content of immediate awareness of a certain subject in a certain mental perspective; and (iii) a cognitive map, which uses an abstract semantic space to represent relations among mental states, schemas and their instances. Components of the eBICA model (Figure 1) include working, semantic, episodic, procedural, and sensory memories, plus a value system and a cognitive map. All details of the BICA model cannot be discussed here. The core framework can be summarized by the following set of self-explanatory tuples, some elements of which can be empty [34,36,37,39]:

- semantic map = (semantic space, mental states and schemas, their allocations)
- mental state = (attributes, schemas)
- schema = (attributes, terminal nodes, internal nodes, links)
- node = (attributes, reference to schema)
- attributes = (category, perspective, attitude, appraisal, bindings, activation, …)

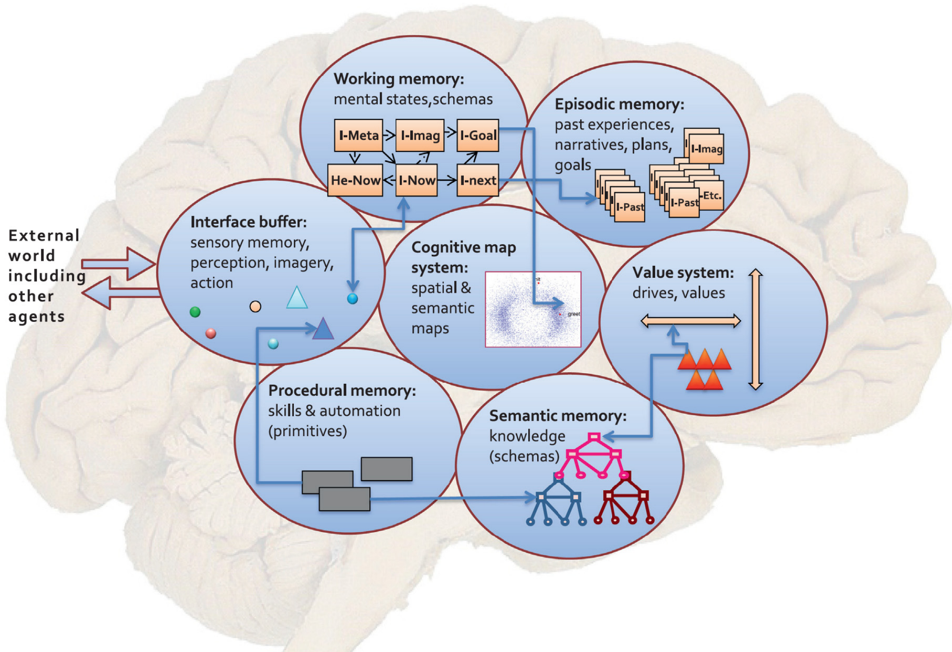

Figure 1: General view of the eBICA model as seven interconnected components. Reproduced with permission from [39].

2.2 The Mapping

Components of the BICA model are roughly mapped onto the brain as follows.

- **Working memory:** activity in ventrolateral prefrontal cortex (VLPFC, BA 45), dorsolateral prefrontal cortex (DLPFC, BA 46), dorsal parietal (BA 9, 46), dorsal frontal (BA 10).
- **Working memory, figural reasoning:** dorsal parietal cortex (BA 7), ventral frontal parietal cortex (BA 40).
- **Cognitive map for episodic and spatial reference memory:** hippocampus, parahippocampal gyrus (entorhinal, perirhinal and retrosplenial cortices), lateral parietal cortex, nuclei of diencephalon.
- **Cognitive map for utility matrix in decision making:** lateral infraparietal cortex (LIP).

- **Value system, absolute value:** orbitofrontal cortex; relative reward value: striatum.
- **Value system, emotional network:** anterior cingulate cortex, amygdala, orbitofrontal cortex, hypothalamus, insula.
- **Episodic memory:** synaptic weights in/between the hippocampus and extrastriate neocortices.
- **Semantic memory:** medial temporal lobe, parahippocampal, prefrontal, parietal cortices.
- **Interface buffer, output and imagery:** premotor and motor cortices, cerebellum.
- **Interface buffer, input and imagery:** primary sensory cortices and related structures of their thalamocortical loops.
- **Procedural memory:** specialized neocortical areas, including visual, auditory, language (Broca, Wernike), motor and premotor cortices and related structures of their thalamocortical loops, plus the cerebellum.

Neurophysiologically, emotional reactions and values are supported by a distributed network of brain structures, including amygdala, nucleus accumbens, anterior cingulate, paracingulate and orbitofrontal cortices, the striatum, hypothalamus, ventral tegmental area, the insula, and are mediated by major neurotransmitters, including dopamine, serotonin, acetylcholine and norepinephrine

2.3 Dynamics and General Prediction

At the core of eBICA dynamics is the standard cognitive cycle including perception, cognition and action. Schemas invoked by sensory input and working memory content populate mental states in working memory and bind to other schemas, resulting in new elements of awareness, intentions and initiation of actions. This picture, as outlined below, captures various aspects of fluid reasoning and generates expectations for physiological measures.

An expectation based on previous studies and the BICA model is that during a challenging cognitive task within the intervention, DMN will be suppressed due to activation of a fluid intelligence network, GFN. As a result, a new network of brain activity GFN will be stabilized over the training period, resulting in an increase of fluid intelligence Gf. The new network may differ by its elements (i.e., topologically) and/or by the distribution of weights of connections. Our intervention will, in various combinations, exercise/train the subnetworks involved in realizing selected mechanisms required for Gf. In order to ensure integration of the necessary cognitive functionality in the network, we include additional elements in the game design.

When the BICA model is solving the N-back task, one active mental state in working memory is used to maintain awareness of each presented item and its expected matching N steps forward (using the schema of an N-back match). When the BICA model is used to solve Raven's Advanced Progressive Matrices (APM), the main cognitive process consists in applying various schemas to the perceived image, which predicts activation of semantic memory, in addition to the activation of working memory. Episodic memory is also used: subjects learn from their experience how to solve matrices. In addition, reasoning about matrices involves spatial cognition, figural reasoning, imagery, and the value system (motivation), thus engaging the corresponding brain areas (see the mapping above). These are general predictions of the eBICA model that will be refined during the pilot study.

When applied to a variable-n-back game paradigm (based on [20]) a version of which will be used in the intervention, BICA model predicts similar patterns of brain activation during execution of the task: primarily including working, semantic and episodic memory components.

In general, we argue that our biologically inspired, causal model of cognition (the eBICA model) accounts for virtually all mechanisms of human higher cognition, in particular, those supporting fluid intelligence, among others, that will be included in our intervention. Examples are:

Inference of the elements of a problem. This may be passive and achievable by simple pattern recognition or it may involve active perturbations to the problem context and statistical bootstrapping.

Inference of the properties/affordances of the elements and their relationships to each other and to the agent. Again, this may be simple and direct or it may require interaction, temporal inferences, etc.

Identification of the objective in terms of the elements of the problem and sub-objectives, such as the satisfaction of constraints and avoidance of obstacles and threats.

Identification of solutions to the objective and sub-objectives. This may involve deduction, inference, planning, anticipating outcomes of interactions and causation.

Working memory mechanisms that maintain the cognitive state and the ability to reason over the elements of the problem space.

Episodic memory mechanisms that for a given situation identify relevant outcomes of past actions providing validation or support of reasoning.

Simultaneous, multi-objective satisfaction and/or threat avoidance.

With such mechanisms, mapped onto the schemas, states, and cognitive maps of the eBICA model, we can then design an appropriate videogame intervention and, using the existing mappings of the eBICA model to neurophysiological measures, make predictions of neuroimaging results and detectable changes due to the intervention.

In order to assist learners in developing supportive motivational beliefs as well as control their cognitions, emotions, and environments while engaging in the task, participants' use of metacognitive, motivational, and behavioral processes need to be assessed. The goal is to determine the degree to which these participants can self-regulate their learning [33,37]. There processes include forethought phase measures which focus on goal-setting, strategy selection and motivational indices that prepare the learner to learn more effectively. They also include performance phase measures used to assess self-control and self-monitor one's behavior and consequences. Finally, self-reflection measures assess a learner's reactions to his or her outcomes. These self-reflections, in turn, influence forethought processes and motivational beliefs regarding subsequent efforts to learn.

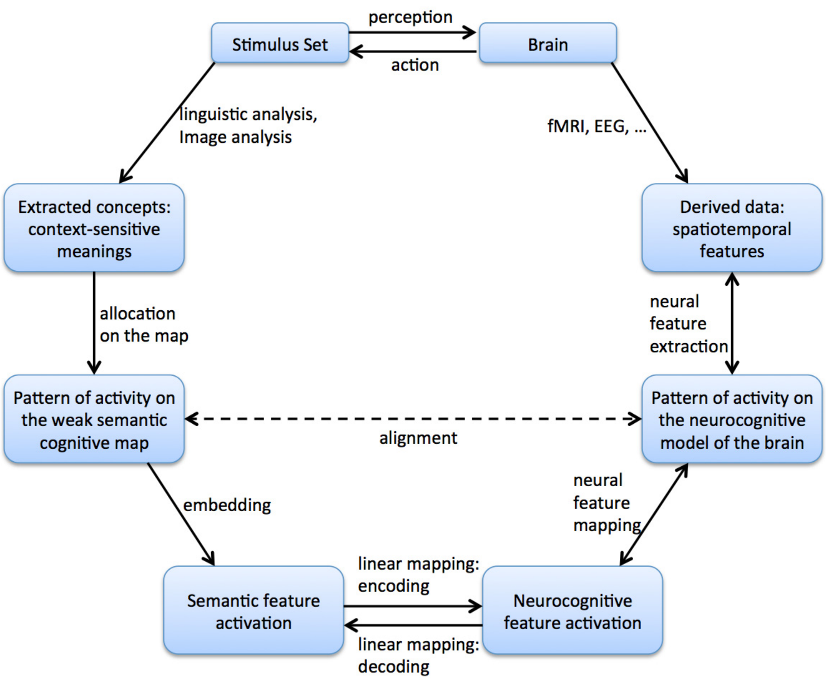

Figure 2: The interpretation of the brain activity in terms of the weak semantic cognitive map, by refining and optimizing the suggested by cognitive neuroscience one-to-one mapping between spatiotemporal patterns of the brain activity and the weak semantic cognitive map domains.

In order to build human-like-efficient tools for data analysis, it is necessary to have a theory of how concepts are represented in the human brain. This theory should specify (a) the structure and semantics of concept representations in the human brain, and (b) types, formats and specific patterns of neuronal activity instantiating these representations. Accordingly, our proposed candidate for the theory includes the following two components.

1. The weak semantic cognitive map (WSCM) that we developed recently for representation and quantification of the word meaning [2,38,40], together with an algorithm of linguistic analysis of text to be used for context-specific extraction of concepts from test materials.

2. Optimized interpretation of spatiotemporal patterns of brain activity in terms of WSCM. Cognitive neuroscience suggests that brain activity is based on an intermediate semantic level of representation, with concepts mainly reduced to their principal semantic dimensions, or "hidden factors". Our previous empirical study [9,10] allows us to predict patterns of brain activity for specific "hidden factors".

We claim that WSCM is a good candidate as a component of the theory of brain representation of concepts, because it is built on the cumulative world-wide human data collected over millennia. This data is the natural language itself, specifically, its synonym-antonym relations represented in many publicly available dictionaries in several languages that we used to construct the map.

Our main hypothesis is that elements of WSCM correspond to spatiotemporal patterns of brain activation detectable by noninvasive imaging techniques (Figure 2). Specifically, there exists an unambiguous interpretation of certain classes of spatiotemporal patterns of brain activation as specific domains on WSCM. Support for this hypothesis comes from multiple studies, starting from classical works of Osgood et al. [27] based on factor analysis of psychometrics, and now including analysis of neuroimaging data [9,10].

To build a unifying cognitive theory of emotions, we need a new framework. The eBICA framework is an elegant way to introduce emotional elements at the core of virtually all basic cognitive process in BICA [39]. Specifically, this framework (i) makes description and processing of emotions in a cognitive system local, (ii) makes certain known clustering of emotions natural, and (iii) adds emotional elements as intrinsic components virtually to every cognitive representation. This latter feature is arguably inspired by the human cognition. Indeed, human cognition and emotions are intimately mixed from birth and develop inseparably [28].

At the core of eBICA is the cognitive map component that is used to organize memories in an abstract space: this could be a map of the physical space, or an abstract semantic space model. The model relevant here is emotional space (also called affective space), representing values and flavors of feelings. Many models of this sort developed through centuries nicely converge to one generalizing framework that we call here weak semantic map. The term was coined by Samsonovich, Goldin, and Ascoli [40], while the process of ''weak semantic cognitive mapping'' was described earlier [32,40].

In addition to the weak semantic map of affective space, emotional cognitive elements are included in the eBICA framework in the form of appraisals: i.e., cognitive evaluations of the emotional value of a mental state, an agent, an action, a relationship, etc. Thus, there are three categories of emotional elements in eBICA, which are new with respect to the prototype architectures:

(1) Semantic map of affective space.

(2) An appraisal, one of the standard set of attributes of mental states and schemas (when an attribute of a mental state – emotional state, or self-appraisal; when an attribute of a schema – appraisal, when an attribute of a moral schema – intended appraisal).

(3) A moral schema, that represents a higher-order appraisal (i.e., an appraisal of appraisals) associated with a certain pattern of appraisal values specified as ''normal'' for this schema.

All three kinds of appraisals – emotional states or self-appraisals of mental states, first-order appraisals (appraisals of objects, facts, events, actions, relations, etc.; as well as appraisals of agent minds and personalities), and moral schemas representing appraisals of appraisals – take values on the weak semantic cognitive map (e.g., the EPA or PAD space). One basic idea underlying the present study is that cognitive architectures should be designed in such a manner that all information processing in them could be regarded as ‘‘emotional’’. In particular, this means that (i) goals should originate from intrinsic emotions rather than from externally given instructions; (ii) emotional components should be essential to any part of the cognitive process in the architecture; and (iii) the outcome of each cognitive process should be captured by a certain emotional state.

Built on eBICA computational models were used in experiments in which the subjects interact with virtual actors controlled model or person (other subjects). The results are published in the Proceedings of the Symposium and the Journal AAAI BICA. This paradigm allows you to test assumptions and mechanisms of emotional thinking underlying cognitive architecture by comparing the behavior of the model and the person, and can be expanded to include non-invasive imaging of the brain. This will allow us to build a much more detailed and accurate model and make it more reliable verification. Experiments with the use of fMRI, EEG and other technique detecting the dynamics of activation of various brain zones would assist to verify or to disprove the model predictions.

3 Materials and Methods

Localization of neural network activity of brain during cognitive tasks can be implemented by using complex recording of neurophysiological parameters (fMRI, EEG, eye-tracking, EKG, myogram, response time of subjects) with subsequent applying a method of dynamic connectivity calculation. Functional magnetic resonance imaging (fMRI) — a most precise in spatial aspect noninvasive method — have especial role in experimental research of human brain [42-44]. During the last decade, more sensitive techniques were developed in fMRI studies to analyze information represented in BOLD (Blood Oxygenation Level Dependent) activity. There are three approaches to studying the neuronal effects of a cognitive intervention using fMRI. The first approach would study the effect of the intervention on the brains default mode network [30]. The first approach is suspect due to a recent meta-study of working memory training brain imaging experiments by Buschkuehl, Jaeggi, and Jonides [20] who conclude that inconsistencies across experiments make it impossible to find a specific neural effect of training. But this may be due to a lack of incentives in working memory training which our BICA model hypothesizes should increase the training effect and reduce the variance in training outcomes. A second approach would study the effect of a cognitive intervention on the activation of specific neural structures as predicted by the eBICA framework, identifying emotions on the basis of neural activation [23]. The third approach is to find areas of the brain that display the neural signature, i.e., changes in the hemodynamic response predicted by the BICA model as the incentives in the working memory task are changed. Since it is unclear at this point in the research which statistical approach should be used we will adopt a design that allows us to make measurements consistent with all three approaches.

For more detailed reconstruction of fMRI activity and its relationships to the input space of image properties, one can use EEG data and eye-tracking data to find regressors and apply them for subsequent spatial localization of brain activity. The possibility of using combined fMRI and EEG studies, where regressors based on EEG were calculated for fMRI, has been successfully demonstrated in works on localization of epileptic spikes [8,47], studying of visual perception [5,26], localization of neural networks of brain at rest [21,25], and localization of neural network sleep states (eg, [7,12,31]). Neural network approach, that involves evaluation of microstates of brain using analysis of EEG amplitude-frequency characteristics which would serve as regressors for fMRI data, was also successfully applied to classifiers of functional states of the brain [41].

In addition to the EEG data, for calculation of fMRI data regressors, eye-tracking data can be used [44]. It should be emphasized that the eye-tracking data also allow us to solve the problem of combined analysis of encoding and decoding of complex visual stimuli: the parameters of eye movements can successfully recover a specific subjective image formed by viewing a complex image

[29]. Oculomotor activity is a sensitive indicator of cognitive processes and dynamics of human interaction with the environment. It is an essential component of the cognitive processes associated with reception, conversion and use of visual information [48]. In contrast to self-report, registration of eye movements provides not only objective, continuous, and detailed information, but also qualitatively new information about the studied phenomena. Thus, the recording and analysis of eye movements as a behavioral method provides access to the internal form of human information processing, which usually proceeds extremely rapidly and unconsciously. These forms of internal activity can be studied with the help of neuroimaging, although examples of the simultaneous use of both approaches are very rare [17]. Studies show [19,13,22,45,46] that the nature of eye movements can be determined: orientation sight and the operational dynamics of the field of view; Strategy Survey perceived scenes; informational complexity of the subject and its accuracy in fixing elements; the search area and "play" solutions to visual-motor tasks; structural units of activity and the level of development activities; status and content of consciousness; the effectiveness of operational tasks and / or execution of individual stages of practice; impairment of the cognitive processes under various diseases and injuries of the brain.

Using such methods, we can now watch time-averaged activity of individual voxels, and dynamics of changes in time, associated with large-scale networks of human brain [1]. This approach has been applied to our fMRI data in this study of human brain activity during cognitive tasks which solving is modulated, for example, by emotional state of the subjects. There are several methods proposed to measure effective connectivity for fMRI study. They are Structural Equation Modeling (SEM, e.g. [4]), Granger Causality Analysis (GCA, e.g. [16]), and Dynamic Causal Modeling (DCM, see [14,15]). DCM, deals with an fMRI time series and models the dynamic effective relationship of nodes at the neuronal level using differential equations. In the course of further development, the opinion starts to prevail that DCM is a more consistent and informative approach to infer causal relationships between brain regions on the basis of fMRI data than others [11,15].

For better recognition of emotional reactions, tomography technology can complement the psycho-physiological measurements, such as electromyography and skin conductance measurements [24].

4 Conclusions

The proposed approach will allow us to validate and refine the suggested approximate mapping of the eBICA model onto the brain, and select the final neurophysiological measures that will be used in the follow-up experimental studies. In the case that we will not reach the desired effect size, the measures and the parameters of the eBICA model will be further fine-tuned based on collected data.

The main result presented here is a description of the information processing level of the dynamics of cognitive and emotional evaluation of other agents and relationships with them in the process of joint activities, broken down into components mapped onto the brain, including their role in decision-making and generation of behavior. This is done based on the selected emotional cognitive architecture eBICA [39].

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